ECE/CSC 776

Traffic Modeling

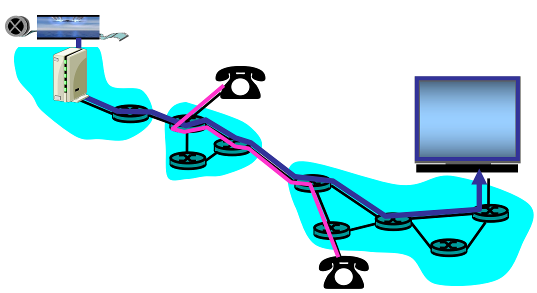
Prof. Michael Devetsikiotis

(with slides from Prof. Nelson Fonseca, State University of Campinas, Brazil)

Motivation

- Driving forces
  - Faster computers
  - Faster lines
  - Integration of *services*, multimedia
  - Top-down service requirements: "QoS"
- How to deliver reliably and efficiently?
  - ATM, IntServ, DiffServ, MPLS, Optical WDM, NGN
- Analysis and design not trivial

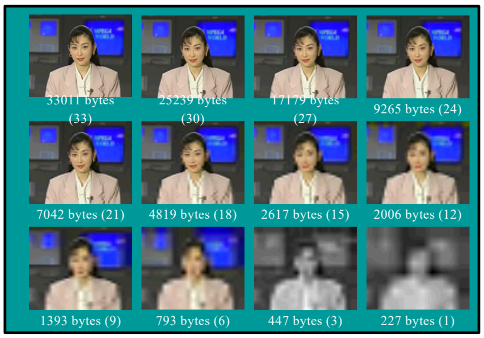
Multimedia Networks



Quality of Service

- "Perception of the quality of the transfer of information expressed by quantitative metrics"
- Services can be "elastic" or "inelastic"
- Most commonly used QoS parameters:
  - Delay
  - Loss rate
- More recently *subjective* measures have been studied with metrics

Quality of Service



Network Technologies

- Several network architectures:
  - ATM: now “legacy” high speed network
  - IntServ: not scalable
  - DiffServ: per class differentiation
  - MPLS: ATM meets IP
  - Optical networks and DWDM, burst switching
  - GMPLS: MPLS meets optical
- Similar challenges: how to allocate *resources*
- Emerging: Wired - Wireless flexible networks
- Also important: Access networks!

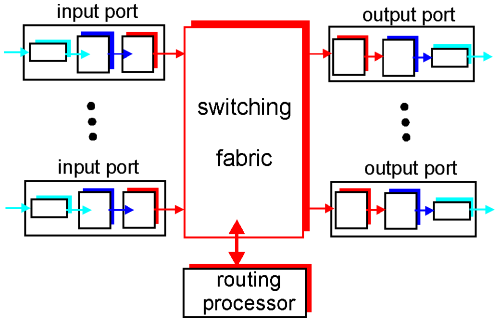
Next Generation Networks

- NGN: ITU’s latest attempt at standardizing the next generation, all-encompassing network
- Emphasizes “services” and openness
- Uses IMS and SIP
- New layers and “strata”
- See, for example, IEEE Communications Magazine, October 2005, and more recent

Switching

- All such approaches require appropriate
  - links
  - nodes (switches, routers, cross-connects)
  - processor sharing (scheduling, routing)
  - switch fabric and memory
- Input vs. Output queueing issues
- Line speed vs. memory speed vs. complexity

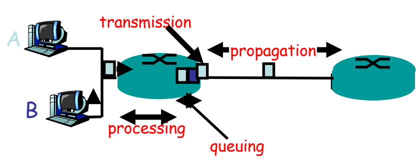
Queuing Delay



Big Picture: Congestion Control

- Preventive
  - Usually for “inelastic” services
  - It prevents the occurrence of congestion using
    - *Call admission control (CAC)*
    - *Policing (GCRA)*
- Reactive
  - Corresponds to “elastic” services
  - It is based on feedback from the network to control transmission rates
    - *Available bit rate (ABR) service*
    - *TCP and variants (with or without Explicit Congestion Notification, ECN)*

Delay



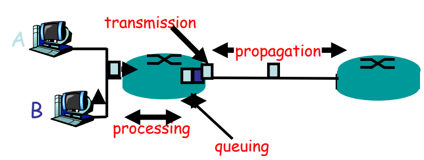
Delay

Transmission delay:

- R=bandwidth (bps)
- L=pkt size (bits)
- delay = L/R

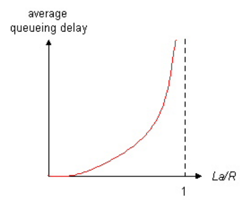
Propagation delay:

- d = link length
- s = propagation speed ($\sim 2 \times 10^8$ m/sec)
- delay = d / s



Queuing Delay

traffic intensity = La/R



Network Workload: "Traffic"

- Telecom networks built to transport *traffic*
- Flow of bytes or packets or messages

Why is Traffic Modeling Important?

- Need for performance evaluation and capacity planning
- Accurate performance prediction requires realistic traffic models
- Can use in analysis or testing ("synthetic traffic")
- Synthetic traffic matches real traces, is more efficient to use
- Most traffic types in high-speed networks are *bursty*
- Burstiness is mainly due to *autocorrelation*
- Renewal models assume autocorrelation away for tractability
- Performance prediction non-realistic without burstiness

Traffic Modeling

Motivation:

Better models required for performance studies in:

QoS, admission control, testing

Goals:

Accurate models of the **statistical behavior** of the traffic

Computationally **efficient** models of the traffic

Our Goal

- To understand relevance of traffic characteristics with respect to network performance and QoS
- Identify and familiarize with common traffic models

Some References

- *Broadband Integrated Networks*, Mischa Schwartz, Prentice Hall PTR, 1996, ISBN 0-13-519240-4.
- "Network Traffic Modeling", N. Fonseca and M. Devetsikiotis, Wiley Encyclopedia of Telecommunications, 2003.
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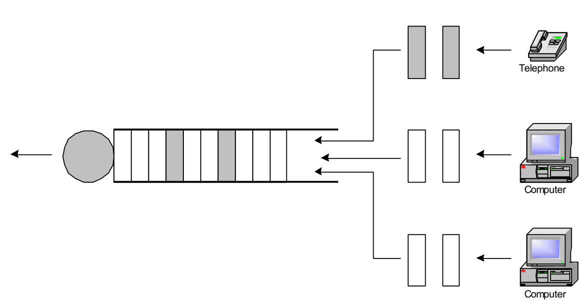
- "Fast, Approximate Synthesis of Fractional Gaussian Noise for Generating Self-Similar Network Traffic", V. Paxson, Comp. Communication Review 27(5), pp. 5-18, Oct. 1997.
- Universal Mobile Telecommunications System (UMTS): Selection procedures for the choice of radio transmission technologies of the UMTS (UMTS 30.03 version 3.2.0), European Telecommunications Standards Institute.
- "Efficient Traffic Generation for Modeling, Management and Verification", Michael Devetsikiotis and John Lambadaris.
- Fractal Simulation Traffic Models for Internet Simulation, B. Ryu and S. Lowen.
- See also
  - "Self-Similar Traffic and Performance Evaluation", eds. K. Park and W. Willinger, Wiley, 2000.
  - Darryl Veitch's web page with papers and characterization software.
  - Rolf Riedi's web site with software related to multifractal traffic.

History and Motivation

- Predict performance of switches
- Telephony: Poisson arrivals and exponential holding
- Good fit, analytically tractable
- Cornerstone of telephone network design: "teletraffic"
- Recall "Math meets the Internet"
- Laws of large numbers, Palm-Khintchine (superposition)
- Homogenous, static, predictable (limited variability)
- Modeling parsimony: average is good enough
- Later: faxes, telephone modems -> holding times?
- More recently: Data files, pictures, multimedia…
- Multiplexing, blocking?

Queuing in Multimedia Networks



Initial analysis

- Example from Schwartz textbook
- Traffic: 5 synchronous streams of 299,040 cells/sec
- Buffer size B, line rate 312,500 cells/sec

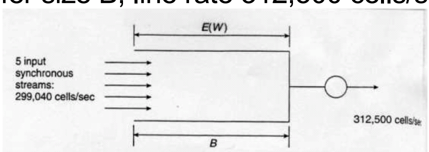


FIGURE 3–1 ■ Model, ATM multiplexing-buffering.

Initial Analysis (cont.)

- G/D/1/B or nD/D/1
  $\rho = 0.957$
  - E(W) = 2.7 μsec
  - W < W_{max} = 4 x 3.2 = 12.8 μsec
  - No losses for B=4 or bigger
- If Poisson: M/D/1, already big difference
  - E(W) = ρ m / 2(1- ρ) = ρ 3.2 /2(1- ρ) = 35.6 μsec!
  - Need B = 249 for cell loss 10^{-9}!
- Conclusion: Mean is not enough; smoothness or burstiness affects a lot

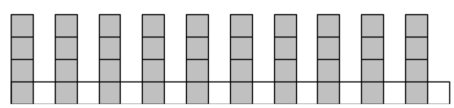
Mean and Variance

$$E[X] = \sum_{X=-\infty}^{\infty} XP\{X\}$$

$$VAR[X] = E[(X - E[X])^2]$$

$$VAR[X] = \sum_{X=-\infty}^{\infty} (X - E[X])^2 P\{X\}$$

Mean and Variance

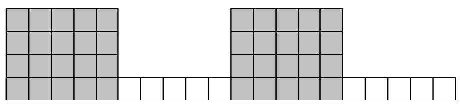


Mean amount of work arrived at each slot = 4

Variance =

$$4.0^2 \text{ x } 0.5 + 4.0^2 \text{ x } 0.5 = 16.0$$

Mean and Variance



Mean amount of work arrived= 4.0

Variance of the amount of work arrived =

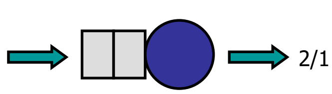
$$4.0^2 \text{ x } 0.5 + 4.0^2 \text{ x } 0.5 = 16.0$$

Mean and Variance

- Both processes have the same mean and variance. But what is their impact on queuing?

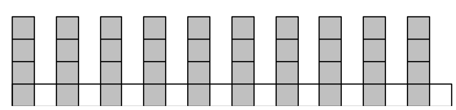
Mean and Variance

- Consider a queue with a server, service rate of two cells per time unit and buffer space of two cells.

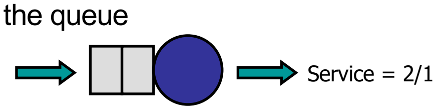


Mean and Variance

When the first stream



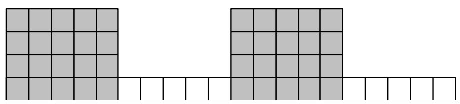
Feeds the queue



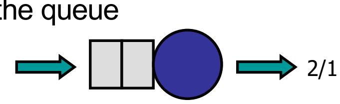
No loss!

Mean and Variance

But when the second flow



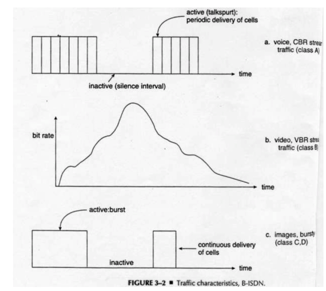
feeds the queue



then 1/5 pkts are lost!

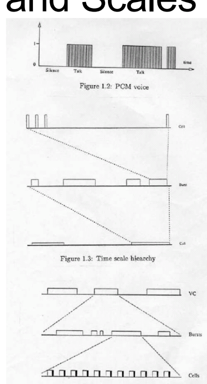
Real Traffic: Scales and Burstiness

- Measurements say traffic is *not* Poisson
- Variable with different time scales



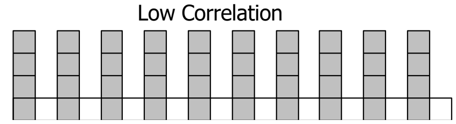
Traffic Bursts and Scales

- Hierarchical view (figure from I. Kaj):
  - Call
  - Burst
  - Packet
- Also “transactions” and “flows”
- How to characterize: Mean? Peak? Variance? Autocorrelation?

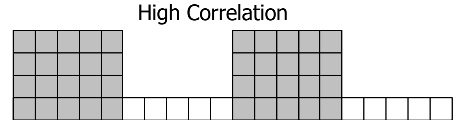


Correlation

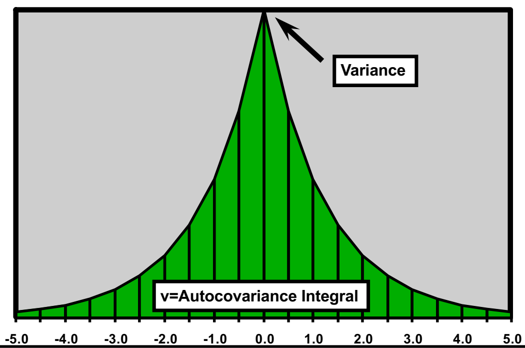
Low Correlation



High Correlation



Autocovariance



Taxonomy of Applications

- Hierarchy of scales and components
- From simple to complex
- Marginal distributions and correlations
- From renewal and memoryless to very correlated and “long range dependent”

Methodology

- Decompose into scales and “modulated processes”
- Measure then statistically *fit*, then validate via goodness-of-fit (recall simulation lectures, input analysis)
- Synthetic generation is step for simulation
- Otherwise analyze with queueing (exact or numerical)

Taxonomy of Models

- See Frost/Melamed, Adas, Devetsikiotis/Fonseca articles
- DES, continuous inter-arrivals vs. discrete time
- Workload, burstiness
  - Renewal and IID: no dependence
  - Phase renewal
  - Markov and embedded Markov: one step memory
  - Markov modulated, On Off, Interrupted Poisson Process etc.
  - Markov renewal modulated
  - Semi Markov
  - MAP
- Other interesting models:
  - Fluid: useful for analysis and also for simulation
  - Regression models – classical statistics
  - Discrete autoregressive (DAR) and modular autoregressive (TES)

Markov Modulated Poisson Process

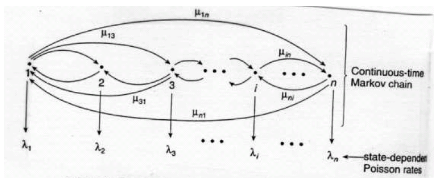


FIGURE 3–11 ■ Markov-modulated Poisson process (selected transitions only shown).

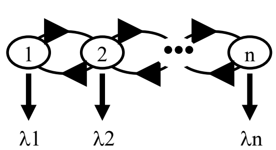
Markov Modulated Poisson Process

$$\Lambda = \begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix}$$

$$\theta = \begin{bmatrix} q_{11} & q_{12} \\ q_{21} & q_{22} \end{bmatrix}$$

Markov Modulated Process

- Arrival rate depends on understanding Markov chain



Markov Modulated Process

Arrivals → single
Arrivals → batch

Time → discrete
Time → continuous

Markov Modulated Process

- Markov Modulated Poisson Process – MMPP (continuous time, single arrival)
- Batch Markovian arrival process – BMAP (continuous time, batch arrival)

Markov Modulated Process

- Discrete Time Batch Markovian Arrival Process – D-BMAP (discrete time, batch arrivals)
- Discrete Time Markovian Arrival Process (D-MAP)

Regression Models

- Autoregressive models

$$X_t = \phi_1 X_{t-1} + \phi_2 X_{t-2} + \cdots + \phi_p X_{t-p} + \varepsilon_t,$$

$$\rho_k = A_1 G_1^k + A_2 G_2^k + \ldots + A_p G_p^p,$$

- TES: Transform-Expand-Sample
  - Uses modulo-1 operations
  - Correlated numbers with desired PDF
  - Marginal by inverse transform
  - Numerical fitting of correlation

$$U_n^+ = \begin{cases} U_0, & n=0 \\ \langle U_{n-1}^+ + V_n \rangle, & n>0 \end{cases} \quad U_n^- = \begin{cases} U_n^+, & n \ \textit{even} \\ 1-U_n^+, & n \ \textit{odd} \end{cases}$$

$$X_n^+ = D(U_n^+), \quad X_n^- = D(U_n^-)$$

- DAR(p), for example p=1: $X_n = V_n X_{n-1} + (1 - V_n) Y_n.$

Voice: The mother of all models

- Simple traffic
- Two states: active and silent
- Basic assumptions hold well
- Models
  - Semi-Markov (periodic arrivals in Markov states)
  - MMPP (Poisson arrivals in Markov states)
  - Fluid model (constant fluid during Markov states)
- Solve? (see Schwartz Ch. 3)

Voice Traffic

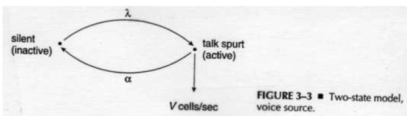


FIGURE 3–3 ■ Two-state model, voice source.

ON-OFF Source

- Alternating periods of silence and of activities
- Voice source:
  - – ON 0.4 – 1.2 sec
  - – OFF 0.6 – 1.8 sec
  - – 170 ATM cells/sec in ON

True MMPP

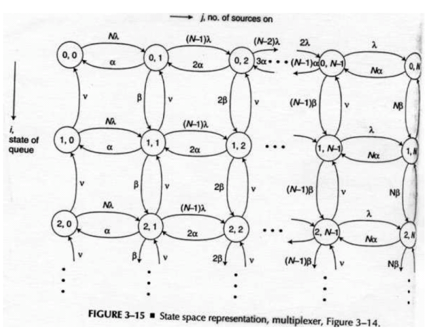
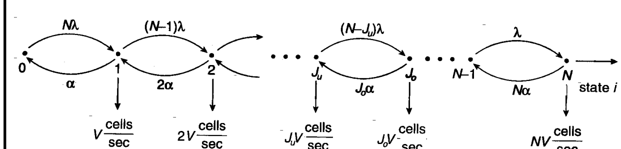
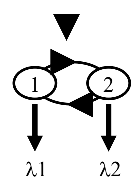


FIGURE 3–15 ■ State space representation, multiplexer, Figure 3–14.

Markov Modulated Fluid





Aggregate of *N* Voice Sources

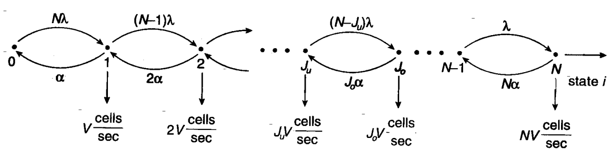


FIGURE 3–5 ■ Composite model, *N* voice sources of Figure 3–4.

Fluid-Flow Equations

$$-C\alpha \frac{dF_0(x)}{dx} = -N\lambda F_0(x) + \alpha F_1(x)$$

$$(1-C)\alpha \frac{dF_1(x)}{dx} = N\lambda F_0(x) - [(N-1)\lambda + \alpha]F_1(x) + 2\alpha F_2(x)$$

$$(2-C)\alpha \frac{dF_2(x)}{dx} = (N-1)\lambda F_1(x) - [(N-2)\lambda + 2\alpha]F_2(x) + 3\alpha F_3(x)$$

$$\vdots$$

$$(N-C)\alpha \frac{dF_N(x)}{dx} = \lambda F_{N-1}(x) - N\alpha F_N(x)$$

Fluid-Flow Equations

- $F_j(x)$ = Prob. [j sources on, buffer occupancy≤x]

$$= \sum_{i=0}^{N} \alpha_i \Phi_{ij} e^{z_i x} \quad 0 \le j \le N$$

Markov Modulated Process

- M/G/1 – type
- Efficient algorithms

$$P = \begin{bmatrix} B_0 & A_0 & 0 & 0 & \dots \\ B_1 & A_1 & A_0 & 0 & \dots \\ 0 & A_2 & A_1 & A_0 & \dots \\ 0 & 0 & A_2 & A_1 & \dots \\ 0 & 0 & 0 & A_2 & \dots \\ . & . & . & . & \dots \\ . & . & . & . & \dots \\ . & . & . & . & \dots \end{bmatrix}$$

$$\lambda = xP$$

M/M/1

$$P = \begin{bmatrix} 1-\lambda & \lambda & 0 & 0 & \dots \\ \mu & 1-\lambda-\mu & \lambda & 0 & \dots \\ 0 & \mu & 1-\lambda-\mu & \lambda & \dots \\ 0 & 0 & \mu & 1-\lambda-\mu & \dots \\ . & . & . & . & \\ . & . & . & . & \\ . & . & . & . & \end{bmatrix}$$

TCP/UDP Traffic

- TCP and related applications
  - FTP
  - TELNET
  - SMTP
- Empirical distributions and inversion
- Interactive and connection setup aspects
- "tcplib" library: hierarchical model based on functionality (see paper)

HTTP and WWW Traffic

- First analyzed by Deng (see paper)
- Hierarchical decomposition:
  - WWW request arrivals
  - ON periods (data activity)
  - OFF periods (thinking times, etc.)
  - Distribution during ON period
- Measure and fit
- Assumptions!
- *Heavy-tailed* distributions: Weibull and Pareto

Game Traffic

- Measurement-based models
- Hierarchical fitting
- Example in paper by Borella: *micro-scale*

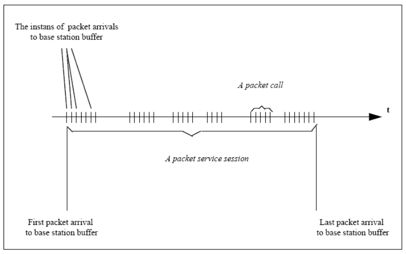
2.3 Algorithm

The overall methodology of this study loosely followed this algorithm:

1. Visually examine the PDF or CDF of the data set and choose an appropriate analytical distribution.
2. Use an MLE technique to fit the data set to the distribution.
3. Example a Q-Q plot of the fit. If the fit deviates for a particular portion of the distribution, consider modeling the data set with a split distribution. If the overall fit is poor, start over with a different analytical distribution.
4. Determine the λ^2 value of the fit.
5. Examine extreme upper tail for deviations.
6. Calculate autocorrelation.

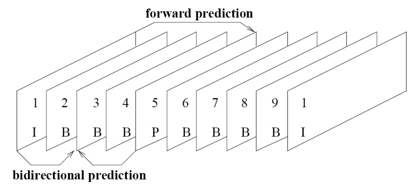
A Real-Life Hierarchical Model

- ETSI model for UMTS (3G) testing

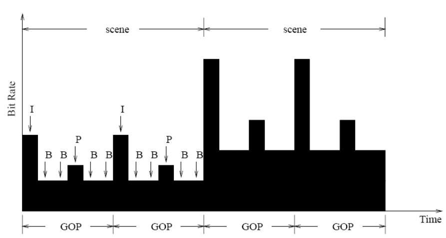


Video: The most bursty traffic!

- Compressed video (MPEG)
- Uses *intra* and *inter*-frame compression
- Based on “frames” and groups-of-pictures (GOP)



Compressed Video (cont.)



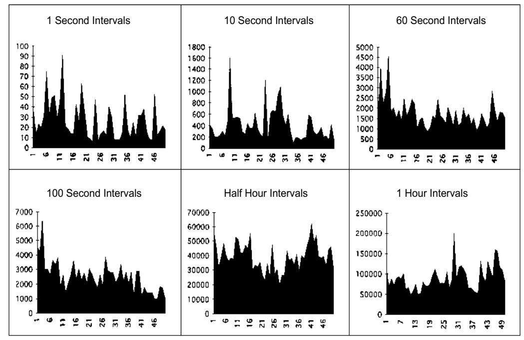
Video Modeling

- MMPP and Markov Modulated fluid models (see Schwartz textbook)
- Autoregressive models
- DAR(1) and TES
- They fit adequately but queuing is imprecise
- In reality, “long range dependent”…

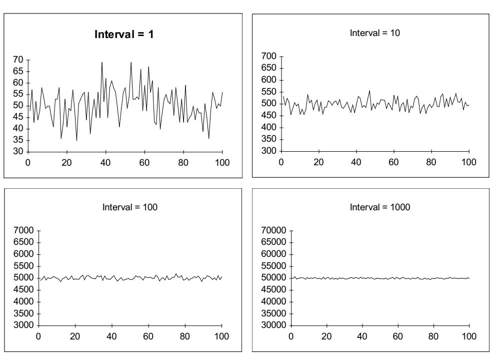
New Era: Self Similarity and LRD

- Observations in early nineties:
  - Scaling in Ethernet traffic
  - Persistence of video traffic
  - Similarly for WAN
- Traffic did not scale or become smoother as expected
- Poisson assumption questioned
- Birth of "self similar" era

Self-Similar Traffic (Ethernet)



Poisson Process



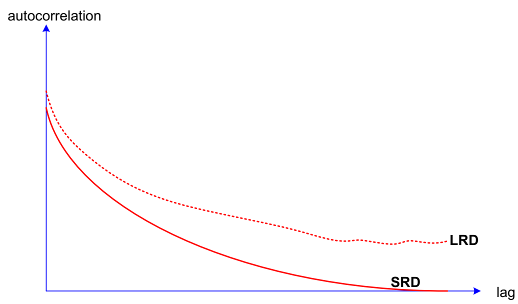
Long Range Dependence

- Hyperbolic decay of autocorrelation

$$r(k) \approx H(2H-1)k^{2H-2} \qquad k \to \infty$$

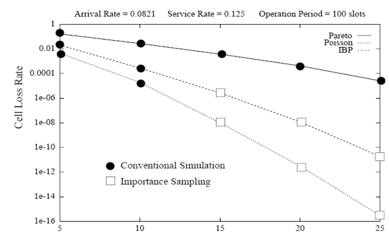
$$\sum_{k=-\infty}^{\infty} r(k) = \infty \qquad if \qquad \frac{1}{2} \langle H \langle 1$$

LRD versus SRD



Impact of Long-Range Dependence

- Implications to network design and control may be crucial
- Self similar models: burstiness across time-scales
- Cell loss probability:



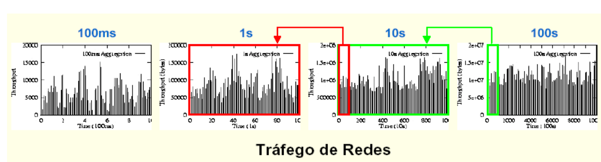
Tail distribution and LRD

$$\frac{\Pr\{Z=\tau\}}{\Pr\{Z\geq\tau\}} \approx 1-e^{-c}$$

$$\frac{\Pr\{Z=\tau\}}{\Pr\{Z\geq\tau\}} = 1-\left(\frac{\tau}{\tau+1}\right)^{\alpha} \rightarrow 1 \quad t\rightarrow\infty$$

Self-Similarity

- By analyzing the number of packets or number of bytes, we observe an invariance of the traffic behavior in differente time-scales, from milliseconds to minutes to even hours:



Self-Similar

- Aggregate Process

$$X^{(m)}(i) = \frac{1}{m} \sum_{t=m(i-1)+1}^{mi} X(t)$$

Self-Similar

- *X(t)* is exactly second-order self-similar with parameter *H* (1/2 < *H* < 1)

$$\gamma(k) = \frac{\sigma^2}{2}((k+1)^{2H} - 2k^{2H} + (k-1)^{2H})$$

- *X(t)* is asymptotically second-order self-similar if

$$\lim_{m\to\infty} \gamma^{(m)}(k) = \frac{\sigma^2}{2}((k+1)^{2H} - 2k^{2H} + (k-1)^{2H})$$

Self-Similar

- Self-similar with stationary increments

$$\gamma(k) = \frac{\sigma^2}{2}(|t|^{2H} - |t-s|^{2H} + |s|^{2H})$$

- The increment process satisfies

$$X =_d m^{1-H} X^{(m)}$$

$$\mathrm{var}(X^{(m)}) = \sigma^2 m^{-\beta}$$

Self-Similar

- The Fractal Brownian Motion is a self similar with Gaussian stationary increments and the increment process is called Fractal Gaussian Noise

Self-Similar

- An aggregate of a large number of on-off sources with Pareto distribution produces an FBM

The Parameter *H*

- The Hurst parameter, *H*, quanitifes the degree of self-similarity in a time-series
- **0.5 < H < 1** : $\sum_{k=-\infty}^{\infty} r(k) \to \infty$ ~~non-summable ⇒ **LRD**~~
- **H = 0.5** : [redacted] summable ⇒ **SRD**
- **0 < H < 0.5** : $\sum_{k=-\infty}^{\infty} r(k) = 0$ not common

The Logscale Diagram

$\alpha = 2H + 1$

- Confidence intervals
- Linear behavior

The Logscale Diagram

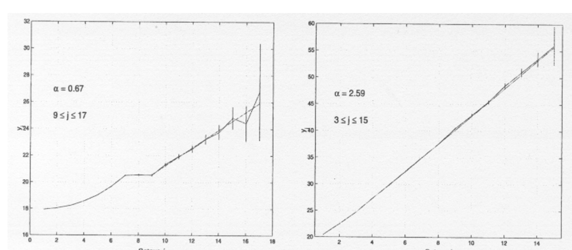
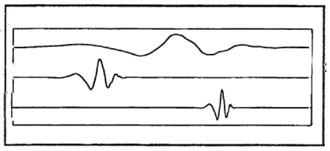


Fig. 2.3 LRD and *H*-sssi behavior in Ethernet traffic data. *Left*: Logscale diagram for the discrete series of successive interarrival times, showing a range of alignments and an α estimate consistent with long-range dependence. *Right*: Logscale diagram for the cumulative work process (bytes up to time *t*), consistent with an asymptotically self-similar (close to exactly self-similar) process with stationary increments.

Wavelet Transform



Wavelets from a length-8 Daubechies filterbank. From top to bottom: $\psi_{0,0}(t)$, $\psi_{1,3}(t)$, $\psi_{3,22}(t)$

- Projecting a signal onto locally oscillating waveforms

Scaling (dilating and compressing) and shifting

$$\psi_{j,k}(t) = 2^{-j/2}\psi(2^{-j}t - k)$$

Wavelet Transforms

$$X(t) = \sum_k C_X(j_0,k)\phi_{j_0,k} + \sum_{j \le j_0}\sum_k d_X(j,k)\psi_{j,k}(t)$$

$C_X(j_0,k)$ – coarse-resolution

$d_X(j,k)$ – wavelet coefficients – finer scales

Logscale Diagram

- Wavelet coefficients and variance of data related
- $$Y_j = \log(\mu_j) = \log\left(\frac{1}{n}\sum_{k=1}^{n_j}\left|d_X(j,k)\right|^2\right)$$
- Logscale diagram ➔ log(Y_j) x Y_j

Multifractal

- At small time scales burstiness does not follow the same pattern at higher scales
- *h*(*t*), Hoelder exponents, highly rearying as a function of *t*

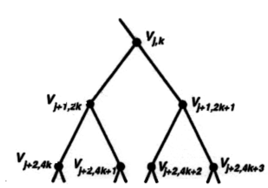
Multiplicative Cascades

- Initial mass is iteratively divided into parts which size is defined by
- Multipliers → random variable → define the weight of each part

Binomial Cascade

- $$X((2k+1)/2^{n+1}) - X(2k/2^{n+1}) \overset{d}{=} \prod_{i=1}^{n+1} M^{i}_{k_i}(X(1)-X(0))$$
- $$M^{n+1}_{2k} + M^{n+1}_{2k+1} = 1$$

Multiscaling Trees



- Binomial cascades – each level of the tree corresponds to a different level of aggregation

Multifractal Brownian Motion

- Generalization of Fractal Brownian Motion
- Gaussian process
- In the neighborhood of *t* an mBm can be approximated by an fBm

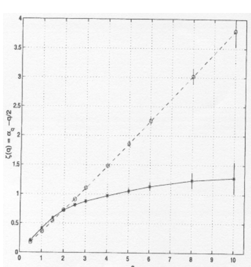
Multiscaling Diagram

$$\mu_j^{(q)} = 1/n_j \sum_k |d_X(j,k)|^q, q \in R$$

- Fractal $$E|X_\delta(t)|^q = C_q |\delta|^{qH}$$
- Multifractal $$E|X_\delta(t)|^q = C_q |\delta|^{(q)}$$

Multiscale Diagram

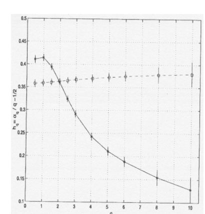
- A lack of alignment in the diagram strongly suggests multifractality



Linear Multiscale Diagram

$$h_q = \alpha_q \big/ q - \frac{1}{2}$$

- Fractal – horizontal line



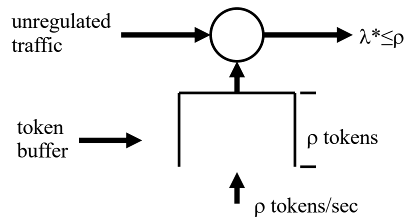
Performance and Queueing

- Needed for admission and QoS calculation
- Exact solution typically impossible
- Classical queueing: approximate fit and numerical solutions
- More modern approach:
  - Effective or equivalent bandwidth
  - Envelope processes
- Upper bound to the amount of traffic arrived
- Deterministic EP → absolute upper bound
- Probabilistic EP → allows violation defined by violation probability

Envelope Processes

$$A(0,t) \le \sigma + \rho t$$

$$\lim_{t \to \infty} \frac{A(0,t)}{t} \le \rho$$



Example of a leaky bucket regulator

ρt+σ

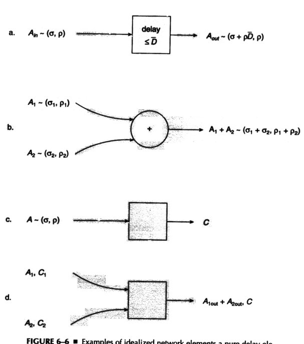


FIGURE 6–6 ■ Examples of idealized network elements a pure delay element b adder c work-conserving element, output capacity C d work-conserving multiplexer.

Fractal Envelope Process

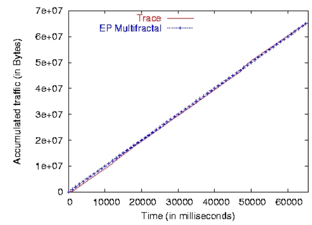
$$\lim_{\rho \to 0^+} \left\{ \frac{W(t+\rho u) - W(t)}{\rho^{H(t)}} \right\}_{u \in R^+} = \left\{ B_{H(t)}(u) \right\}_{u \in R^+}$$

Multifractal Envelope Process

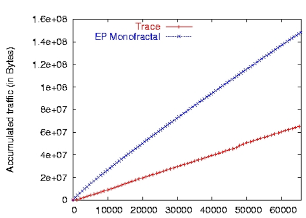
$$\hat{A}(t) = \int_0^t \bar{a} + \kappa\sigma H(x) x^{H(x)-1} dx$$

$$\hat{A}(t) = at + \kappa\sigma t^H$$

Multifractal Envelope Process



Multifractal Envelope Process



Envelope Process of an Aggregate of Multifractal Flows

$$\hat{A}(t) = \int_0^T \sum_{i=1}^{N} \bar{a}_i + \kappa \left(\sum_{i=1}^{N} \sigma_i^2 H_i(x) x^{2H_i(x)-1} \right) \left(\sum_{i=1}^{N} \sigma_i^2 x^{2H_i(x)} \right)^{-\frac{1}{2}} dx$$

Equivalent Bandwidth

$$\kappa\left(\sum_{i=1}^{N}\sigma_i^2 H_i(t)t^{2H_i(t)-1}\right)\left(\sum_{i=1}^{N}\sigma_i^2 t^{2H_i(t)}\right)^{-\frac{1}{2}} = C - \sum_{i=1}^{N}\bar{a}_i$$